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Melody Way: Visualizing Influence, Collaboration, and Genre Evolution in the Music Industry

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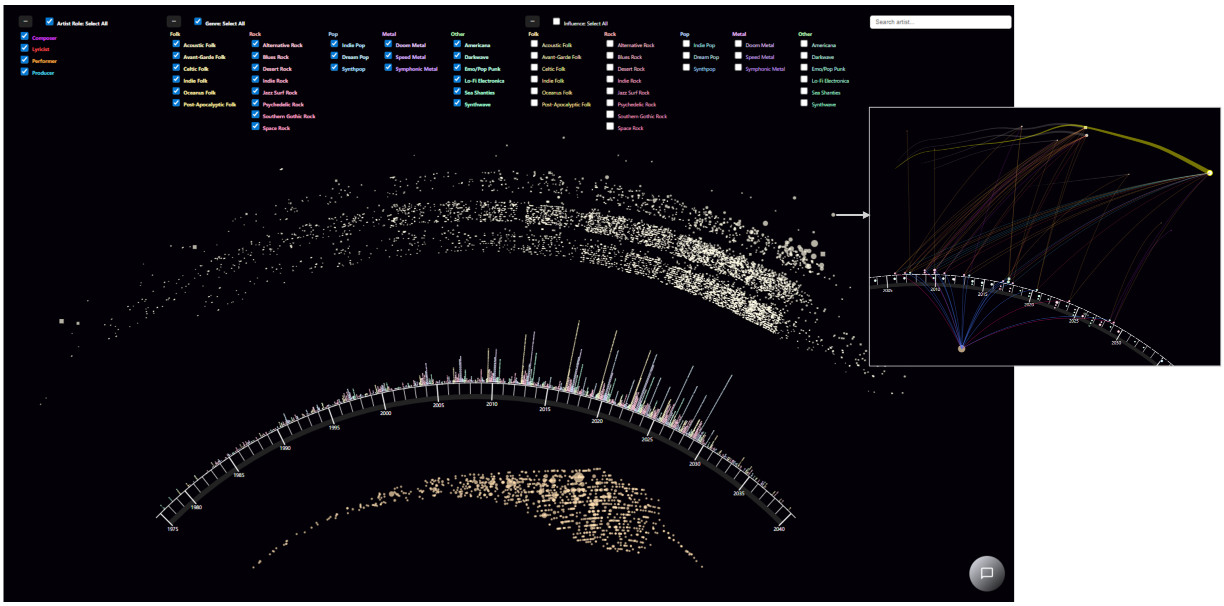

Figure 1: Overview of *Melody Way*. Artists are arranged in a radial galaxy where angle encodes latest release year and radius reflects influence band and productivity. A curved timeline arc plots songs and albums by release year (position) and genre (color). Albums are larger nodes, songs smaller; white-centered nodes are notable artworks, black/empty ones are non-notable. Artworks are sorted by type and notability within each year. Yellow nodes below timeline mark record labels. The view supports zooming and panning. Inset (right): Clicking an artist reveals "tails" that trace influence paths and collaboration links connecting the artist to co-creators, enabling quick inspection of a career.

Abstract

We present Melody Way, a visual analytics system for exploring influence, collaboration, and genre evolution in the music industry. The system integrates temporal and network perspectives in a coordinated multi-view environment, enabling analysts to move fluidly between high-level trend analysis and detailed relationship exploration. Interactive filters, search, and an AI chatbot support targeted investigation and predictive queries, with results visually verified in context. Applied to the 2025 VAST Challenge MC-1 dataset, Melody Way revealed evolving genre dynamics, distinctive artist trajectories, and potential future leaders in Oceanus Folk, demonstrating how integrated visual and AI-assisted analysis can illuminate complex patterns in large cultural datasets.

Index Terms: Radial layout, influence analysis, temporal visualization.

1 Introduction

Understanding influence and collaboration in the music industry requires integrating multiple perspectives, such as temporal trends, network relationships, and contextual roles into a single analytical workflow. Conventional node–link diagrams and timelines, when used in isolation, often fail to preserve both the detailed network structure and the broader temporal context [1]. These challenges are amplified with large-scale knowledge graph datasets, where showing all entities and links at once can overwhelm the display and obscure meaningful patterns.

Melody Way addresses these by combining a radial "galaxy" layout with a coordinated timeline view and a selection-based network view, temporal influence tails, filters, search, and an AI chatbot. This design maintains a clear overview while allowing analysts to drill into specific artists, artworks, and relationships without losing context. By integrating time, influence, and role information in a single dashboard, the tool supports both broad trend exploration

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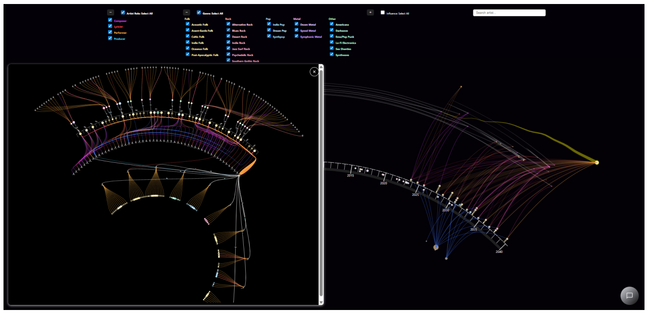

Figure 2: Overview of Sailor Shift's creative network. Left: expanded ego view showing all of Sailor's connections, Right: Sailor (gold node) and her collaborators. The upward-sloping yellow "tail" (2024 → 2040) marks her rising influence, and the dense web of links highlights the breadth of her collaborations and impact.

and detailed relationship tracing across tens of thousands of interconnected entities.

2 System Overview

2.1 Data Processing

We augment the dataset by aggregating and computing attributes in the 2025 VAST Challenge Mini-Challenge 1 (MC-1) dataset [2]. Temporal context uses each artwork's release year. For each artist, the year-y influence score is the weighted sum of influence edges on artworks released in year y. Heuristic weights: CoverOf 1.0, DirectlySamples 0.9, LyricalReferenceTo 0.8, InterpolatesFrom 0.7, InStyleOf 0.6.

Although the schema defines influence links as artwork → artwork, some links (including all from Sailor) are artist → artist. These are retained as provided and grouped by type for scoring and visualization. For artists with only artist → artist influence links (e.g., Sailor), we distribute the total influence evenly across their artwork's release years to obtain yearly scores.

2.2 Galaxy of Stars

Figure 1 shows an overview of Melody Way. The artists are positioned in a radial "galaxy." Angle encodes the year of the artist's most recent release. Radial tier (which band) encodes cumulative (all-years) influence. The plotted radius is the band's baseline plus a small within-band offset proportional to productivity (more artworks → slightly farther out). Below, a curved timeline arc plots songs and albums by release year (position) and genre (color). The visual encodings for the type of artwork, notability, and label affiliation are detailed in Figure 1. The view supports zooming and panning for exploration.

2.3 Selection-Based Network Views

Selecting or searching for an artist expands collaboration links in the galaxy and opens a pop-out panel (Figure 2 left) with the artist's ego-network spanning collaboration and influence relations. This view supports close examination of direct and indirect connectivity, making explicit collaboration and implicit influence readily apparent. Yearly influence scores (defined in section 2.1) are shown as temporal "tails" (Figure 2, right). Clicking an artwork highlights its contributing artists and linked record labels in the galaxy, connecting temporal events to network structure.

2.4 Interactions

Facet filters (role, genre, influence path) refine the visible elements. In the influence filter, selecting specific genres shows a line chart of yearly influenced artworks; selecting all genres shows yearly pie

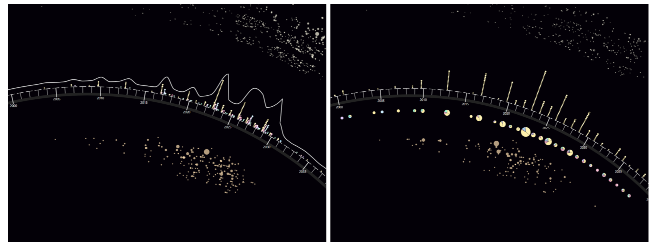

Figure 3: Genre influence dynamics for Oceanus Folk. Left: influence from Oceanus Folk to all genres over time, with peaks marking major creative surges. Right: influence on Oceanus Folk from all genres, shown as yearly pie charts where each slice indicates the proportional contribution of an influencing genre.

charts of influence proportions from each genre to the target. These summaries reveal temporal shifts in genre influence. A search box supports direct artist lookup, returning their artworks, collaborators, and influence paths. The AI chatbot, implemented with the OpenAI API and dataset-specific prompts, enables natural-language queries about artists, artworks, and relationships, complementing visual exploration with concise summary information.

3 Storytelling

With Melody Way analysts could quickly identify artists' career trajectories, collaboration patterns, and temporal shifts in genre influence. As shown in Figure 2, selecting `Sailor Shift` opens a pop-out panel (Figure 2, left) showing her ego-network of collaborations and influence links, while the main galaxy view (Figure 2, right) highlights her artworks and collaborators over time. The upward-sloping yellow "tail" indicating her growing influence over time and the highlighted links connecting her to her artworks, resembling a meteor shower, reveal the breadth of her collaborations and impact. Genre influence dynamics (Figure 3) show the intermittent impact of `Oceanus Folk` and the shifting mix of genres contributing to its evolution. To explore potential future Oceanus Folk stars, analysts can query the integrated AI chatbot with criteria: post-2035 activity, growing collaboration networks, creative roles, and ties to Oceanus-focused labels. Suggested candidates can then be further examined in Melody Way, using filters and linked visualizations to verify and contextualize their connections, genre involvement, and career arcs.

4 Conclusion

Melody Way illustrates how integrating temporal and network perspectives in a coordinated multi-view environment can address the challenges of analyzing large cultural knowledge graphs. Through linked visualizations, filtering, and AI-assisted exploration, it revealed Sailor Shift's diverse influences, the evolution of Oceanus Folk, and potential future leaders in the genre from the 2025 VAST Challenge MC-1 dataset. Future work could adapt the approach to other cultural domains, showing how integrated temporal-network visual analytics can uncover complex influence dynamics in large-scale datasets beyond the music industry.

References

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